Department of Economics and Finance

Working Paper No. 2203

Economics and Finance Working Paper Series

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February 2022

http://www.brunel.ac.uk/economics

PERSISTENCE IN THE PASSION INVESTMENT MARKET

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February 2022

Abstract

This paper uses R/S analysis and fractional integration techniques to investigate persistence in the passion investment market. Specifically, it analyses 3 fine wine price indices, 10 diamond price indices, 15 art price indices, and 1 stamp price index at the daily, monthly and quarterly frequency. The results can be summarised as follows: wine prices are found to be highly persistent, whilst stamp prices appear to be only weakly persistent, though they can still be characterised as a long-memory process; as for diamond prices, they can be persistent (Diamonds & Gems), anti-persistent (Diamonds Carat indices) or even random (Polished Prices Diamond Index). The dynamic R/S analysis also shows that persistence is time-varying and tends to fluctuate around the average. These findings can be explained by the different degree of liquidity of the assets examined.

Keywords: *Passion Investment; Persistence; Long Memory; R/S Analysis; Fractional Integration*

JEL Classification: *C22, G12*

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** Alex Plastun gratefully acknowledges financial support from the Ministry of Education and Science of Ukraine (0121U100473).

1. Introduction

"Passion investing" in non-traditional assets one is passionate about, such as fine wines, diamonds, stamps, and art objects, has become increasingly popular over the last few decades as an effective way for achieving portfolio diversification. According to Bernales et al. (2020), in 2017 the art and collectibles market attracted more than 35% of high-net-worth individuals. Some of passion collectibles such as diamonds and art objects are used as collateral for obtaining funds (Bernales et al., 2020). Besides being useful as a store of value (similarly to gold), they can be considered as "emotional" consumption assets, which makes them play a dual utility role (both as investment and consumption assets) for both passionate investors and speculators; these have fluctuating tastes and enthusiasm for such assets as well as heterogeneous beliefs resulting in large forecast dispersion for the expected value of the 'emotional' income.

Compared to conventional assets, emotional or passionate ones are also more likely to be constrained by limited supply and are generally characterised by higher transaction costs, lower liquidity, informational asymmetry (e.g., insiders such as auction houses often have access to more relevant information), and market inefficiencies accentuated by the design of the auction trading system (Ashenfelter and Graddy, 2011) and the difficulty to apply a short selling strategy. As argued by Aye et al. (2018), the ability of investors in the art market to earn abnormal returns by exploiting predictable price patterns points to the inefficiency of this market; in this respect passionate assets do not differ from conventional ones, for which there is plenty of evidence of persistence in returns and their volatility (Caporale et al., 2019), price bubbles (Scherbina and Schlusche, 2014) and of various types of market anomalies such as calendar ones (Plastun et al, 2020), all suggesting that the Efficient Market Hypothesis (EMH – Fama, 1970) might not hold empirically.

Various studies on passion assets have recently been carried out to examine, for instance, their performance relative to conventional assets (Veld and Veld-Merkoulova, 2007 for stamps; Dimson & Spaenjers, 2014 for stamps and art objects); the diversification benefits of purchasing fine wines (Chu, 2014; Bouri, 2014, 2015; Jurevičienė & Jakavonytė, 2015; Bouri et al., 2018) and diamonds (D'Ecclesia & Jotanovic, 2018; Barbi et al., 2020); the (in)efficiency of the fine wine market (e.g., Bouri et al., 2017; Fernandez-Perez et al., 2019; Masset and Henderson, 2010). As for the persistence of passion asset prices, mixed evidence has been obtained by the following studies: Goetzman (1995), for painting sales data from 1716 to 1986; Aye (2017), Munteanu and Pece (2015) and Ameur and Le Fur (2019), for the art market; Chong et.al. (2012), Auer (2013) and Auer and Schuhmaher (2013), for diamonds; Bouri et.al. (2016), Ameur and Le Fur (2019) and Kumar (2021), for fine wines.

The present paper aims to provide more thorough evidence on persistence in the passion market by examining a wide range of price indices (more precisely, 3 for fine wine prices, 10 for diamond prices, 15 for art prices, and 1 for stamp prices) at the daily, monthly and quarterly frequency using two different long-memory methods, specifically R/S analysis and fractional integration. The layout of the paper is the following. Section 2 provides a brief review of the relevant literature. Section 3 describes the data and outlines the empirical methodology. Section 4 presents the empirical results. Section 5 provides some concluding remarks.

2. Literature Review

Persistence in a variety of financial markets has been examined in numerous studies. For instance, Baillie et.al (2007) found long memory in daily futures returns for commodities (gold, gasoline, cattle, hogs, soybeans, corn). Volatility persistence was detected by Jin and Frichette (2004) and Saphton (2009) in the case of agricultural future prices, and by Saleem (2014) for gold and silver returns. Gil-Alana et. al. (2015) found persistence in gold prices. Evidence of long memory was also provided by Khuntia and Pattanayak (2018) and Caporale et al. (2018) in the case of daily Bitcoin returns, and by by Zhou and Kang (2011), Zhou (2016), Liu et.al.(2019) for REITs (Real estate investment trusts).

Analysing persistence is particularly interesting in the case of the passion market, which is likely to be characterised by lower efficiency than other financial markets owing to higher information asymmetry, difficulties with the valuation of the assets reflecting disagreements between the buyer and the seller (Bernales et al., 2020), higher transaction costs and lower trading volumes, high entry barriers and investment risks (Fischer and Firer, 1985), and difficulties in implementing short selling strategies. Thus a number of studies on this topic have been conducted.

Goetzman (1995) analysed painting sales data from 1716 to1986 and found that decennial returns exhibit persistence, possibly because of their correlation with inflation, which is positively autocorrelated. Aye (2017) examined long memory in 15 art price indices using fractional integration methods that account for long memory; his findings imply market efficiency only for a few cases characterised by high liquidity, globalisation, improved flow of information, and a high number of participants. Persistent price behaviour and market inefficiency in the art market was also reported by Assaf et al. (2021). Munteanu and Pece (2015) analysed the stock prices of the four main auction houses and concluded that three of them exhibit persistence and one anti-persistence. Volatility persistency of volatility was found by Ameur and Le Fur (2019).

Chong et.al. (2012) investigated instead persistence in daily returns and their volatility for diamonds ranging from 0.3 to 3 Carat (from law quality to flawless); their evidence suggests that long memory is present only in the estimated volatility. Similar results were obtained also by Auer (2013) and Auer and Schuhmaher (2013). Persistence in the wine market was found by Bouri et.al. (2016), Ameur and Le Fur (2019), Kumar (2021); autoregressive properties were reported by Fernandez-Perez et al. (2019), whilst mean reversion was detected by Bouri et al. (2017).

3. Data and Methodology

Our sample includes the following series at the daily, monthly and quarterly frequency: 3 fine wine price indices (Liv-ex Bordeaux 500 Index, Liv-ex Fine Wine 100 Index and Liv-ex Fine Wine Investables Index) over the period 1991-2021; 10 diamond price indices (Diamonds-1 Carat Commercial Index, Diamonds-1 Carat Mixed Index, Diamonds-0.3 Carat Mixed Index, Diamonds-1 Carat Fine Index, Diamonds-0.3 Carat Commercial Index, Diamonds-0.3 Carat Fine Index, Diamonds-0.5 Carat Commercial Index, Diamonds-0.5 Carat Fine Index, Diamonds-0.5 Carat Mixed Index and Polished Prices Diamond Index) over the period 1989-2021 in the case of the first 3 indices, and 2001-2021in the case of the last 7; 15 art price indices (Global Index in USD, Global Index in EUR, Painting, Sculpture, Photography, Drawing, Print, Old Masters, 19th Century, Modern Art, Post-War, Contemporary, USA in USD, UK in GBP and France in EUR) over the period 1998-2021; 1 stamp index (Stanley Gibbons Stamp Index) over the period 1989-2021. The data sources are London International Vintners Exchange (Liv-ex), Fairfield County Diamonds (https://www.diamondse.info/), Artprice (Artprice.com), and the Stanley Gibbons group (ww.stanleygibbons.com/publishing/gibbons-stamp-monthly), respectively.

To evaluate persistence two different methods are applied: R/S analysis (both static and dynamic) and fractional integration. The former is based on the Hurst exponent which is the measure of persistence lying in the interval [0, 1]. Persistence is found when

H > 0.5. Random data are characterised instead by H = 0.5. Anti-persistence is detected when H < 0.5.

The Hurst exponent H is the estimated slope coefficient in the following equation: *log (R / S) = log (c) + H*log (n)* (Hurst, 1951). More precisely, the estimation procedure is the following:

1. The original data set is transformed into a data set $N_i$consisting of log returns:

$$N_i = log\left(\frac{Close_t}{Close_{t-1}}\right), t = 1,2,\ldots(M-1). \quad (1)$$

2. This data set is divided into contiguous A sub-data sets with length n, such that $A_n = N$, then each sub-data set is identified as I_a, given the fact that $a = 1, 2, 3. . . , A$. Each element I_a is represented as N_k with $k = 1, 2, 3. . . , N$. For each I_a with length n the average e_a is defined as:

$$e_a = \frac{1}{n}\sum_{k=1}^{n} N_{k,a}, k = 1,2,3,\ldots N, a = 1,2,3\ldots, A. \quad (2)$$

3. Accumulated deviations $X_{k,a}$ from the average e_a for each sub-period I_a are calculated as:

$$X_{k,a} = \sum_{i=1}^{k}(N_{i,a} - e_a). \quad (3)$$

The range is defined as the maximum index $X_{k,a}$ minus the minimum $X_{k,a}$, within each sub-period (I_a):

$$R_{Ia} = max(X_{k,a}) - min(X_{k,a}), 1 \le k \le n. \quad (4)$$

4. The standard deviation S_{Ia} is calculated for each sub-period I_a:

$$S_{Ia} = \left((\frac{1}{n})\sum_{k=1}^{n}(N_{k,a} - e_a)^2\right)^{0,5}. \quad (5)$$

5. Each range R_{Ia} is normalised by dividing by the corresponding S_{Ia}. Therefore, the re-normalised scale during each sub-period I_a is R_{Ia}/S_{Ia}. In step 2 above,

adjacent sub-data sets of length n are obtained. Thus, the average R/S for length n is defined as:

$$(R/S)_n = (1/A)\sum_{i=1}^{A}(R_{Ia}/S_{Ia}). \qquad (6)$$

6. The length n is increased to the next higher level, *(M - 1)/n*, and must be an integer number. In this case, n-indices that include the start and end points of the time series are used, and Steps 1 - 6 are repeated until n = *(M - 1)/2*.

To perform dynamic R/S analysis a sliding-window approach is used (see Caporale et al., 2016 for more details). Specifically, the Hurst exponent is calculated using a data window based on a given number of observations (300 in the present case) which is shifted various times till reaching the end of the sample, the size of the shift being 50 (Caporale et al., 2016). For example, for a data set including 1200 observations there will be 18 shifts ((1200-300)/50) and 19 estimates of the Hurst exponent will be obtained.

The second method employs I(d) techniques to measure persistence as the differencing parameter d which is related to the Hurst exponent described above through the relationship H = d + 0.5. Note, however, that we conduct the R/S analysis for the return series (the first differences of the logged indices), while I(d) models are estimated for the logged indices themselves, in which case the relationship becomes H = (d – 1) + 0.5 = d – 0.5. We consider processes of the form:

$$(1 - B)^d x_t = u_t, \qquad t = 1, 2, ..., \qquad (7)$$

where B is the backshift operator ($Bx_t = x_{t-1}$); u_t is an I(0) process (which may incorporate weak autocorrelation of the AR(MA) form) and x_t stands for the errors of a regression model of the form:

$$y_t = \beta_0 + \beta_1 t + x_t; \qquad t = 1, 2, ..., \qquad (8)$$

where y_t denotes the log of the stock index in each case, β_0 and β_1 denote the constant and the coefficient on a linear time trend t to be estimated, and the regression errors x_t are

I(d). Note that under the Efficient Market Hypothesis the value of d in (7) should be equal to 1 and u_t should be a white noise process. We use both parametric and semi-parametric methods, in the former case assuming uncorrelated (white noise) error and in the latter autocorrelated errors specified as in Bloomfield (1973). More specifically, we use the Whittle estimator of d in the frequency domain (Dahlhaus, 1989; Robinson, 1994, 1995), as described, for example, in Gil-Alana and Robinson (1997).

4. Empirical Results

The static Hurst exponent for the Wine and Stamp indices is reported in Table 1.

Table 1. Static Hurst exponent calculations for the Wine and conventional Stamp indices

Type	Instrument	Hurst exponent
Wine	Liv-ex Bordeaux 500 Index	0.78
	Liv-ex Fine Wine 100 Index	0.85
	Liv-ex Fine Wine Investables Index	0.78
Stamps	STANLEY GIBBONS GROUP	0.59

As can be seen, high values of the Hurst exponent provide evidence of both persistence and long memory in wine prices. Stamps prices are less persistent, but still exhibit long memory.

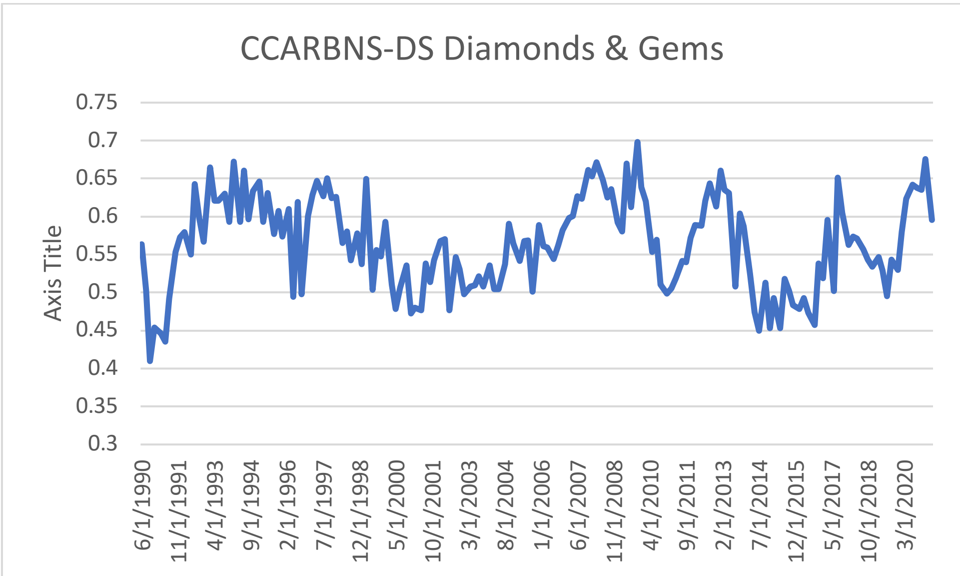
The static Hurst exponent for the Diamond indices is reported in Table 2. As can be seen, these results are mixed, ranging from persistence (in the case of the Diamonds & Gems) to anti-persistence (for the Diamonds Carat indices) and even randomness (for the Polished Diamond Price index), which possibly reflects different degrees of liquidity.

Table 2. Static Hurst exponent calculations for the Diamond indices

Type	Instrument	Hurst exponent
Diamonds	CCARBNS-DS Diamonds & Gems - PRICE INDEX	0.61
	NORCS-DS Diamonds & Gems - PRICE INDEX	0.60
	WORLD-DS Diamonds & Gems - PRICE INDEX	0.60
	Diamonds-1 Carat Commercial Index - PRICE INDEX	0.35
	Diamonds-1 Carat Mixed Index - PRICE INDEX	0.45
	Diamonds-0.3 Carat Mixed Index - PRICE INDEX	0.46
	Diamonds-1 Carat Fine Index - PRICE INDEX	0.36
	Diamonds-0.3 Carat Commercial Index - PRICE INDEX	0.40
	Diamonds-0.3 Carat Fine Index - PRICE INDEX	0.32
	Diamonds-0.5 Carat Commercial Index - PRICE INDEX	0.38
	Diamonds-0.5 Carat Fine Index - PRICE INDEX	0.31
	Diamonds-0.5 Carat Mixed Index - PRICE INDEX	0.42
	Polished Prices Diamond Index - PRICE INDEX	0.51

The next step is the dynamic R/S analysis, which provides information about changes in persistence over time. The results are plotted in Figure 1. Visual inspection suggests that persistence is time-varying and tend to fluctuate around its average.

Figure 1. Dynamic Hurst exponent calculations for the case of CCARBNS-DS Diamonds & Gems



The static Hurst exponent for the Art price indices is reported in Table 3.

Table 3. Static Hurst exponent calculations for the Art price indices

Type	Instrument	Hurst exponent
Artprice	Global Index (USD)	0.43
	Global Index (EUR)	0.39
	Painting	0.54
	Sculpture	0.57
	Photography	0.33
	Drawing	0.65
	Print	0.50
	Old Masters	0.36
	19th Century	0.39
	Modern Art	0.53
	Post-War	0.50
	Contemporary	0.37
	USA (USD)	0.54
	UK (GBP)	0.35
	France (EUR)	0.61

A summary of results is presented in Table 4, where indices are grouped by their degree of persistence.

Table 4. Summary of the results for the static Hurst exponent

Anti-persistent	**Random**	**Persistent**
< 0.45	**0.45 - 0.55**	**> 0.55**
• Diamonds-1 Carat Commercial Index • Diamonds-1 Carat Mixed Index • Diamonds-1 Carat Fine Index • Diamonds-0.3 Carat Commercial • Diamonds-0.3 Carat Fine Index • Diamonds-0.5 Carat Commercial • Diamonds-0.5 Carat Fine Index • Diamonds-0.5 Carat Mixed Index • Artprice Global Index (USD) • Artprice Global Index (EUR) • Photography • Old Masters • 19th Century • Contemporary • Artprice UK (GBP)	• Diamonds-0.3 Carat Mixed Index • Polished Prices Diamond Index • Painting • Print • Modern Art • Artprice Post-War • Artprice USA (USD)	• Liv-ex Bordeaux 500 Index • Liv-ex Fine Wine 100 Index • Liv-ex Fine Wine Investables Index • CCARBNS-DS Diamonds & Gems • NORCS-DS Diamonds & Gems • STANLEY GIBBONS GROUP • Sculpture • Drawing • Artprice France (EUR)

Persistence implies predictability (and therefore represents evidence of market inefficiency), which suggests that autoregressive models can be used to predict prices, whilst anti-persistence indicates that the series revert to their mean more often than a random series would. To shed further light on these issues we report in Table 5 partial correlation functions with the corresponding t-statistics and p-values for all the indices under investigation.

Table 5. Partial autocorrelations: the case of Liv-ex Fine Wine Investables Index, Diamonds-0.5 Carat Fine Index and Diamonds-0.5 Carat Fine Index

Time lag k	Liv-ex Fine Wine Investables Index (persistent)			Diamonds-0.5 Carat Fine Index (anti-persistent)			Polished Prices Diamond Index (random)		
	PACF	T-STAT	P-value	PACF	T-STAT	P-value	PACF	T-STAT	P-value
1	0.99	18.86	0.00	0.97	69.71	0.00	0.99	70.72	0.00
2	-0.06	-1.15	0.13	0.23	16.76	0.00	0.46	32.73	0.00
3	-0.05	-0.88	0.19	0.14	10.36	0.00	0.28	19.82	0.00
4	-0.03	-0.55	0.29	0.14	10.10	0.00	0.19	13.36	0.00
5	-0.01	-0.22	0.41	0.09	6.54	0.00	0.74	52.89	0.00
6	-0.01	-0.14	0.44	0.11	7.83	0.00	-0.53	-37.82	0.00
7	-0.02	-0.31	0.38	0.09	6.66	0.00	-0.03	-2.35	0.01
8	-0.01	-0.22	0.41	0.08	5.43	0.00	0.06	4.59	0.00
9	-0.01	-0.26	0.40	0.13	9.51	0.00	0.11	8.06	0.00
10	-0.01	-0.14	0.44	0.11	8.07	0.00	0.29	20.43	0.00

As can be seen, in the case of the persistent series (Liv-ex Fine Wine Investables Index, Hurst exponent = 0.78) $p<0.05$ implies the presence of an autocorrelation structure with one lag only, whilst for the anti-persistent (Diamonds-0.5 Carat Fine Index, Hurst exponent = 0.31) and random (Polished Prices Diamond Index, Hurst exponent = 0.51) series the p-values for all the first 10 lags are below 0.05, which represents further evidence of autocorrelation.

Additional evidence is obtained using I(d) techniques. Specifically, we estimate the model given by equations (7) and (8) and report the results for the two cases of white noise and autocorrelated errors, in the latter case using the exponential spectral model of Bloomfield (1973). This is a non-parametric method to capture autocorrelation implicitly using the spectral density function, and it has been shown to describe well weak dependence in the context of fractional integration (see, e.g., Gil-Alana, 2004).

In what follows we consider the model given by Equations (8) and (7), i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (1 - L)^d x_t = u_t, \qquad t = 0, 1, \ldots, \tag{9}$$

where y_t is the observed time series, L is the lag operator and u_t is an I(0) process assumed to be in turn white noise or autocorrelated as in Bloomfield (1973).

The results based on the assumption of white noise errors are reported in Table 6 for wines and stamps, Table 7 for diamonds, and Table 8 for art prices. More specifically, Tables 6a, 7a and 8a report the estimated values of d along with their 95% confidence intervals for the three specifications normally considered in the unit root literature, namely: 1) no deterministic terms, 2) a constant only, and 3) a constant and a linear time trend; the coefficients in bold in these tables are the estimates from the preferred models selected on the basis of the statistical significance of the coefficients on the deterministic terms – these are shown in Tables 6b, 7b and 8b together with the corresponding value of d.

It can be seen from Table 6 that in the case of wines and stamps the time trend is always insignificant and the estimated values of d are much higher than 1, which implies that mean reversion does not occur and thus shocks have permanent effects.

Table 6a: Estimates of d: White noise errors

Wines and stamps
i) Wines

Series	No deterministic terms	An intercept	An intercept and a linear time trend
Liv-ex Bordeaux 500 Index	1.11 (1.02, 1.19)	**1.49 (1.39, 1.63)**	1.49 (1.38, 1.63)
Liv-ex Fine Wine 100 Index	1.27 (1.17, 1.59)	**1.52 (1.42, 1.63)**	1.52 (1.42 1.63)
Liv-ex Fine Wine Investables Index	1.48 (1.39, 1.59)	**1.52 (1.43, 1.63)**	1.52 (1.43, 1.63)
ii) Stamps			
STANLEY GIBBONS GROUP	1.08 (1.04, 1.11)	**1.18 (1.14, 1.21)**	1.18 (1.14, 1.21)

In bold the selected specification for each series according to the statistical significance of the deterministic terms. In parenthesis the 95% confidence intervals.

Table 6b: Estimated coefficients in Table 5a

Wines and stamps			
i) Wines			
Series	d (95% conf. intv.)	Intercept (t-value)	Trend (t-value)
Liv-ex Bordeaux 500 Index	1.49 (1.39, 1.63)	93.056 (22.70)	---
Liv-ex Fine Wine 100 Index	1.52 (1.42, 1.63)	100.495 (37.36)	---
Liv-ex Fine Wine Investables Index	1.52 (1.43, 1.63)	20.509 (6.52)	---
ii) Stamps			
STANLEY GIBBONS GROUP	1.18 (1.14, 1.21)	111.988 (64.53)	----

The values in parenthesis in column 2 are the 95% confidence intervals, while those in columns 3 and 4 are the t-statistics for the coefficients on the constant and the time trend respectively.

In the case of diamonds (Table 7) the time trend is negative and significant for six out of the thirteen indices examined, and, in contrast to wine and stamps, mean reversion occurs in most cases, the exceptions being CCARBNS, NORCS and WORLD. The lowest values of d (and thus, the fastest mean reversion in response to shocks) are estimated for Diamonds-1 Carat Fine (0.56) and Diamonds-0.5 Carat Fine (0.58).

Table 7a: Estimates of d: White noise errors

Diamonds			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
CCARBNS-DS Diamonds & Gems - PRICE INDEX	1.00 (0.98, 1.02)	**1.02 (0.99, 1.05)**	1.02 (0.99, 1.05)
NORCS-DS Diamonds & Gems - PRICE INDEX	1.00 (0.98, 1.02)	**1.02 (0.99, 1.05)**	1.02 (0.99, 1.05)
WORLD-DS Diamonds & Gems - PRICE INDEX	1.00 (0.98, 1.02)	**1.03 (1.01, 1.06)**	1.03 (1.01, 1.06)
Diamonds-1 Carat Commercial Index - PRICE INDEX	0.97 (0.95, 1.00)	0.61 (0.59, 0.63)	**0.61 (0.59, 0.63)**
Diamonds-1 Carat Mixed Index - PRICE INDEX	0.99 (0.96, 1.02)	0.78 (0.75, 0.81)	**0.78 (0.75, 0.81)**
Diamonds-0.3 Carat Mixed Index - PRICE INDEX	1.00 (0.97, 1.03)	**0.94 (0.91, 0.97)**	0.94 (0.91, 0.97)
Diamonds-1 Carat Fine Index - PRICE INDEX	0.96 (0.94, 0.99)	0.56 (0.55, 0.58)	**0.56 (0.54, 0.58)**
Diamonds-0.3 Carat Commercial Index - PRICE INDEX	0.99 (0.97, 1.02)	**0.78 (0.76, 0.80)**	0.78 (0.75, 0.80)
Diamonds-0.3 Carat Fine Index - PRICE INDEX	0.97 (0.94, 1.00)	0.60 (0.58, 0.62)	**0.60 (0.58, 0.62)**
Diamonds-0.5 Carat Commercial Index - PRICE INDEX	0.99 (0.96, 1.01)	0.68 (0.66, 0.70)	**0.68 (0.66, 0.70)**
Diamonds-0.5 Carat Fine Index - PRICE INDEX	0.97 (0.94, 1.00)	0.58 (0.56, 0.61)	**0.58 (0.56, 0.61)**
Diamonds-0.5 Carat Mixed Index - PRICE INDEX	1.00 (0.97, 1.03)	**0.87 (0.84, 0.89)**	0.87 (0.84, 0.89)
Polished Prices Diamond Index - PRICE INDEX	1.00 (0.97, 1.03)	**0.90 (0.88, 0.92)**	0.90 (0.88, 0.92)

In bold the selected specification for each series according to the statistical significance of the coefficients on the deterministic terms. In red evidence of mean reversion at the 5% level.

Table 7b: Estimated coefficients in Table 6a

Diamonds			
Series	d (95% conf. intv.)	Intercept (t-value)	Trend (t-value)
CCARBNS-DS Diamonds & Gems - PRICE INDEX	**1.02 (0.99, 1.05)**	8.5557 (273.88)	---
NORCS-DS Diamonds & Gems - PRICE INDEX	**1.02 (0.99, 1.05)**	8.5565 (271.18)	---
WORLD-DS Diamonds & Gems - PRICE INDEX	**1.03 (1.01, 1.06)**	8.5988 (314.30)	---
Diamonds-1 Carat Commercial Index - PRICE INDEX	**0.61 (0.59, 0.63)**	4.8323 (243.27)	-0.00003 (-4.03)
Diamonds-1 Carat Mixed Index - PRICE INDEX	**0.78 (0.75, 0.81)**	5.1473 (259.15)	-0.00023 (-2.08)
Diamonds-0.3 Carat Mixed Index - PRICE INDEX	**0.94 (0.91, 0.97)**	4.7517 (581.66)	---
Diamonds-1 Carat Fine Index - PRICE INDEX	**0.56 (0.54, 0.58)**	4.9088 (229.20)	-0.00004 (-2.46)
Diamonds-0.3 Carat Commercial Index - PRICE INDEX	**0.78 (0.76, 0.80)**	4.9011 (306.45)	---
Diamonds-0.3 Carat Fine Index - PRICE INDEX	**0.60 (0.58, 0.62)**	4.8731 (205.96)	-0.00008 (-3.52)
Diamonds-0.5 Carat Commercial Index - PRICE INDEX	**0.68 (0.66, 0.70)**	4.8436 (247.36)	-0.00006 (-1.92)
Diamonds-0.5 Carat Fine Index - PRICE INDEX	**0.58 (0.56, 0.61)**	4.8963 (232.06)	-0.00008 (-4.03)
Diamonds-0.5 Carat Mixed Index - PRICE INDEX	**0.87 (0.84, 0.89)**	4.6348 (470.04)	---
Polished Prices Diamond Index - PRICE INDEX	**0.90 (0.88, 0.92)**	8.5980 (314.30)	---

The values in parenthesis in column 2 are the 95% confidence intervals, while those in columns 3 and 4 are the t-statistics for the coefficients on the constant and the time trend respectively.

Finally, for art prices (Table 8), the time trend is not significant in any case and the estimates of d are significantly higher than 1 in almost all cases, the only two exceptions being the global indices (USA, EUR).

Table 8a: Estimates of d: White noise errors

Artprices índices			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
Global Index (USD)	0.68 (0.57, 0.81)	**0.60 (0.52, 0.72)**	0.61 (0.53, 0.73)
Global Index (EUR)	0.66 (0.55, 0.79)	**0.47 (0.39, 0.59)**	0.49 (0.40, 0.60)
Painting	1.21 (1.06, 1.43)	**1.52 (1.28, 1.95)**	1.52 (1.28, 1.96)
Sculpture	1.10 (0.96, 1.33)	**1.53 (1.23, 2.01)**	1.53 (1.23, 2.04)
Photography	1.03 (0.84, 1.37)	**1.02 (0.79, 1.52)**	1.02 (0.81, 1.52)
Drawing	1.18 (0.94, 1.53)	**1.39 (1.03, 2.13)**	1.39 (1.03, 2.16)
Print	1.45 (1.21, 1.78)	**1.80 (1.42, 2.35)**	1.80 (1.41, 2.32)
Old Masters	0.94 (0.65, 1.49)	**0.79 (0.48, 1.45)**	0.79 (0.46, 1.45)
19th Century	1.15 (0.97, 1.44)	**1.28 (0.97, 1.87)**	1.28 (0.96, 1.88)
Modern Art	1.02 (0.88, 1.25)	**1.27 (1.03, 1.81)**	1.27 (1.03, 1.81)
Post-War	1.56 (1.30, 1.91)	**1.55 (1.29, 1.98)**	1.53 (1.28, 1.95)
Contemporary	0.87 (0.63, 1.24)	**0.88 (0.63, 1.45)**	0.88 (0.64, 1.46)
USA (USD)	1.20 (1.06, 1.43)	**1.52 (1.28, 1.95)**	1.51 (1.28, 1.96)
UK (GBP)	1.06 (0.94, 1.26)	**1.11 (0.98, 1.35)**	1.11 (0.99, 1.33)
France (EUR)	1.12 (0.99, 1.34)	**1.28 (1.10, 1.64)**	1.27 (1.10, 1.60)

In bold the selected specification for each series according to the statistical significance of the coefficients on the deterministic terms. In red evidence of mean reversion at the 5% level.

Table 8b: Estimated coefficients in Table 7a

Artprices índices			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
Global Index (USD)	0.60 (0.52, 0.72)	114.322 (6.83)	---
Global Index (EUR)	0.47 (0.39, 0.59)	123.751 (12.08)	---
Painting	1.52 (1.28, 1.95)	96.996 (16.61)	---
Sculpture	1.53 (1.23, 2.01)	98.934 (19.32)	---
Photography	1.02 (0.79, 1.52)	99.985 (6.93)	---
Drawing	1.39 (1.03, 2.13)	98.691 (6.89)	---
Print	1.80 (1.42, 2.35)	92.487 (9.92)	---
Old Masters	0.79 (0.48, 1.45)	111.054 (3.99)	---
19th Century	1.28 (0.97, 1.87)	97.396 (13.43)	---
Modern Art	1.27 (1.03, 1.81)	101.858 (11.78)	---
Post-War	1.55 (1.29, 1.98)	89.494 (4.06)	---
Contemporary	0.88 (0.64, 1.46)	107.172 (2.72)	---
USA (USD)	1.52 (1.28, 1.95)	97.032 (16.56)	---
UK (GBP)	1.11 (0.98, 1.35)	98.956 (17.24)	---
France (EUR)	1.28 (1.10, 1.64)	97.343 (19.72)	---

The values in parenthesis in column 2 are the 95% confidence intervals, while those in columns 3 and 4, are the t-statistics for the coefficients on the constant and time trend respectively.

Next we consider the results based on the assumption of autocorrelated errors modelled as in Bloomfield (1973). Table 8, 9, and 10 present the evidence for wine and stamps, diamonds, and art prices respectively, and are structured in the same way as for the case of white noise disturbances. As can be seen, the findings for fine wines (Table 9) are consistent with the previous ones for the white noise case (Table 6): for all four indices the time trend is found to be insignificant and d is estimated to be significantly higher than 1.

Table 9a: Estimates of d: Bloomfield autocorrelated errors

Wines and stamps			
i) Wines			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
Liv-ex Bordeaux 500 Index	0.96 (0.81, 1.15)	**1.37 (1.20, 1.58)**	1.35 (1.20, 1.58)
Liv-ex Fine Wine 100 Index	0.97 (0.83, 1.13)	**1.32 (1.17, 1.55)**	1.32 (1.17, 1.54)
Liv-ex Fine Wine Investables Index	0.99 (0.80, 1.13)	**1.29 (1.19, 1.44)**	1.29 (1.18, 1.44)
ii) Stamps			
STANLEY GIBBONS GROUP	1.01 (0.96, 1.06)	**1.03 (0.99, 1.07)**	1.03 (0.99, 1.07)

In bold the selected specification for each series according to the statistical significance of the coefficients on the deterministic terms. In red evidence of mean reversion at the 5% level.

Table 9b: Estimated coefficients in Table 8a

Wines and stamps			
i) Wines			
Series	d (95% conf. intv.)	Intercept (t-value)	Trend (t-value)
Liv-ex Bordeaux 500 Index	1.37 (1.20, 1.58)	4.608 (344.81)	---
Liv-ex Fine Wine 100 Index	1.32 (1.17, 1.55)	4.534 (233.86)	---
Liv-ex Fine Wine Investables Index	1.29 (1.19, 1.44)	3.020 (123.17)	---
ii) Stamps			
STANLEY GIBBONS GROUP	1.03 (0.99, 1.07)	4.718 (140.69)	---

The values in parenthesis in column 2 are the 95% confidence intervals, while those in columns 3 and 4 are the t-statistics for the coefficients on the constant and the time trend respectively.

For diamonds (Table 10) the time trend is found to be statistically significant (and negative) in 6 out of the 13 cases examined, and mean reversion now occurs in all cases in comparison to 10 out of 13 under the assumption of white noise errors (Table 7).

Table 10a: Estimates of d: Bloomfield autocorrelated errors

Diamonds			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
CCARBNS-DS Diamonds & Gems - PRICE INDEX	0.98 (0.95, 1.03)	**0.86 (0.82, 0.91)**	0.86 (0.82, 0.91)
NORCS-DS Diamonds & Gems - PRICE INDEX	0.98 (0.95, 1.03)	**0.88 (0.83, 0.91)**	0.88 (0.83, 0.91)
WORLD-DS Diamonds & Gems - PRICE INDEX	0.99 (0.95, 1.03)	**0.88 (0.84, 0.92)**	0.88 (0.84, 0.92)
Diamonds-1 Carat Commercial Index - PRICE INDEX	1.00 (0.94, 1.05)	0.64 (0.62, 0.67)	**0.63 (0.61, 0.66)**
Diamonds-1 Carat Mixed Index - PRICE INDEX	1.00 (0.94, 1.05)	0.81 (0.78, 0.84)	**0.80 (0.77, 0.84)**
Diamonds-0.3 Carat Mixed Index - PRICE INDEX	0.99 (0.95, 1.04)	**0.87 (0.82, 0.90)**	0.87 (0.81, 0.90)
Diamonds-1 Carat Fine Index - PRICE INDEX	0.98 (0.95, 1.03)	0.63 (0.60, 0.65)	**0.63 (0.60, 0.65)**
Diamonds-0.3 Carat Commercial Index - PRICE INDEX	0.99 (0.95, 1.04)	**0.75 (0.72, 0.79)**	0.75 (0.72, 0.79)
Diamonds-0.3 Carat Fine Index - PRICE INDEX	0.98 (0.94, 1.03)	0.59 (0.55, 0.61)	**0.58 (0.55, 0.61)**
Diamonds-0.5 Carat Commercial Index - PRICE INDEX	0.97 (0.93, 1.02)	0.66 (0.64, 0.69)	**0.66 (0.64, 0.69)**
Diamonds-0.5 Carat Fine Index - PRICE INDEX	0.96 (0.92, 1.00)	0.59 (0.57, 0.61)	**0.59 (0.57, 0.61)**
Diamonds-0.5 Carat Mixed Index - PRICE INDEX	0.99 (0.95, 1.03)	**0.88 (0.84, 0.92)**	0.88 (0.84, 0.92)
Polished Prices Diamond Index - PRICE INDEX	1.00 (0.96, 1.04)	**0.93 (0.90, 0.95)**	0.93 (0.90, 0.95)

In bold the selected specification for each series according to the statistical significance of the coefficients on the deterministic terms. In red evidence of mean reversion at the 5% level.

Table 10b: Estimated coefficients in Table 10a

Diamonds			
Series	d (95% conf. intv.)	Intercept (t-value)	Trend (t-value)
CCARBNS-DS Diamonds & Gems - PRICE INDEX	**0.86 (0.82, 0.91)**	7.7202 (319.49)	---
NORCS-DS Diamonds & Gems - PRICE INDEX	**0.88 (0.83, 0.91)**	7.7199 (311.76)	---
WORLD-DS Diamonds & Gems - PRICE INDEX	**0.88 (0.84, 0.92)**	7.0521 (306.46)	---
Diamonds-1 Carat Commercial Index - PRICE INDEX	**0.63 (0.61, 0.66)**	**4.8404 (256.73)**	-0.00005 (-2.11)
Diamonds-1 Carat Mixed Index - PRICE INDEX	**0.80 (0.77, 0.84)**	**5.0516 (306.08)**	-0.00013 (-2.01)
Diamonds-0.3 Carat Mixed Index - PRICE INDEX	**0.87 (0.82, 0.90)**	4.7584 (548.97)	---
Diamonds-1 Carat Fine Index - PRICE INDEX	**0.63 (0.60, 0.65)**	**4.8977 (207.64)**	-0.00005 (-1.64)
Diamonds-0.3 Carat Commercial Index - PRICE INDEX	**0.75 (0.72, 0.79)**	4.8997 (293.77)	---
Diamonds-0.3 Carat Fine Index - PRICE INDEX	**0.58 (0.55, 0.61)**	4.8778 (201.03)	-0.00009 (-3.69)
Diamonds-0.5 Carat Commercial Index - PRICE INDEX	**0.66 (0.64, 0.69)**	4.8419 (238.06)	-0.00006 (-1.92)
Diamonds-0.5 Carat Fine Index - PRICE INDEX	**0.59 (0.57, 0.61)**	**4.9008 (213.31)**	-0.00010 (-3.98)
Diamonds-0.5 Carat Mixed Index - PRICE INDEX	**0.88 (0.84, 0.92)**	4.6347 (437.32)	---
Polished Prices Diamond Index - PRICE INDEX	**0.93 (0.90, 0.95)**	4.7251 (947.21)	---

The values in parenthesis in column 2 are the 95% confidence intervals, while those in columns 3 and 4 are the t-statistics for the coefficients on the constant and the time trend respectively.

Finally, for art prices, the time trend is significant for 8 out of the 13 series investigated (more specifically, positive in 5 cases and negative in 3). Mean reversion (d

< 1) is found in 10 out of the 13 cases, and the I(0) hypothesis cannot be rejected for Old Masters and Contemporary.

Table 11a: Estimates of d: Bloomfield autocorrelated errors

Art prices indices			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
Global Index (USD)	0.95 (0.71, 1.26)	**0.93 (0.75, 1.22)**	0.94 (0.77, 1.21)
Global Index (EUR)	0.93 (0.70, 1.25)	**0.89 (0.65, 1.25)**	0.89 (0.70, 1.24)
Painting	0.91 (0.69, 1.23)	**0.86 (0.75, 1.02)**	0.86 (0.75, 1.02)
Sculpture	0.90 (0.68, 1.21)	**0.65 (0.54, 0.84)**	0.65 (0.51, 0.84)
Photography	0.89 (0.67, 1.18)	0.41 (0.31, 0.53)	**0.34 (0.21, 0.47)**
Drawing	0.90 (0.67, 1.27)	0.42 (0.31, 0.54)	**0.16 (0.01, 0.40)**
Print	0.93 (0.69, 1.23)	0.57 (0.43, 0.75)	**0.55 (0.42, 0.74)**
Old Masters	0.67 (0.40, 0.95)	0.03 (-0.10, 0.21)	**-0.07 (-0.22, 0.10)**
19th Century	0.97 (0.83, 1.13)	1.32 (1.17, 1.55)	**1.32 (1.17, 1.54)**
Modern Art	0.87 (0.67, 1.16)	**0.43 (0.28, 0.61)**	0.41 (0.25, 0.59)
Post-War	0.88 (0.66, 1.24)	0.83 (0.74, 0.98)	**0.81 (0.71, 0.95)**
Contemporary	0.97 (0.73, 1.32)	0.31 (0.21, 0.41)	**-0.05 (-0.19, 0.13)**
USA (USD)	0.91 (0.69 1.23)	**0.86 (0.75, 1.02)**	0.86 (0.75, 1.02)
UK (GBP)	0.92 (0.68 1.22)	0.77 (0.68 0.89)	**0.75 (0.65 0.88)**
France (EUR)	0.91 (0.70 1.21)	**0.80 (0.69 0.94)**	0.80 (0.69 0.94)

In bold the selected specification for each series according to the statistical significance of the coefficients on the deterministic terms. In red evidence of mean reversion at the 5% level.

Table 11b: Estimated coefficients in Table 11a

Art prices indices			
Series	No deterministic terms	An intercept	An intercept and a linear time trend
Global Index (USD)	0.93 (0.75, 1.22)	4.610 (38.85)	---
Global Index (EUR)	0.89 (0.65, 1.25)	4.620 (43.69)	---
Painting	0.86 (0.75, 1.02)	4.626 (136.26)	---
Sculpture	0.65 (0.54, 0.84)	4.645 (150.31)	---
Photography	0.34 (0.21, 0.47)	4.771 (97.30)	0.0059 (6.75)
Drawing	0.16 (0.01, 0.40)	4.764 (159.08)	0.0062 (11.79)
Print	0.55 (0.42, 0.74)	4.744 (84.72)	0.0088 (6.89)
Old Masters	-0.07 (-0.22, 0.10)	4.870 (110.75)	-0.0072 (-8.65)
19th Century	1.32 (1.17, 1.54)	4.754 (114.69)	-0.0027 (-3.19)
Modern Art	0.43 (0.28, 0.61)	4.654 (169.23)	---
Post-War	0.81 (0.71, 0.95)	4.657 (68.67)	0.0155 (4.67)
Contemporary	-0.05 (-0.19, 0.13)	4.994 (126.83)	0.0141 (19.24)
USA (USD)	0.86 (0.75, 1.02)	4.619 (136.26)	---
UK (GBP)	0.75 (0.65 0.88)	4.638 (150.81)	0.0052 (4.31)
France (EUR)	0.80 (0.69 0.94)	4.649 (143.95)	---

Values in parenthesis in column 2 are 95% confidence intervals, while in columns 3 and 4, they are tvalues for the deterministic terms (contant, column 3; time trend, column 4). In red evidence of mean reversion at the 5% level.

5. Conclusions

This paper explores persistence in the passion investment market. More specifically, it uses R/S analysis (both static and dynamic) and fractional integration techniques to analyse persistence of the following asset prices at the daily, monthly and quarterly frequency: 3 fine wine price indices, 10 diamond price indices, 15 art price indices, and 1 stamp price index. The results can be summarised as follows. Wine prices are found to be highly persistent, whilst stamp prices appear to be only weakly persistent, though they can still be characterised as a long-memory process; as for diamond prices, they can be persistent (Diamonds & Gems), anti-persistent (Diamonds Carat indices) or even random (Polished Prices Diamond Index). The dynamic R/S analysis also shows that persistence is time-varying and tends to fluctuate around the average. These findings can be explained by the different degree of liquidity of the assets examined.

In the majority of cases the evidence appears to contradict the Efficient Market Hypothesis: persistence implies predictability, and anti-persistence more frequent mean reversion than in the case of random series, and in fact in both cases we show that an autocorrelation structure is present in those series. These findings might not be entirely surprising if one considers the fact that "passion" is a key driver of this type of investment in addition to standard reasons such as portfolio diversification etc.

References

Ameur, B.H., & Fur, E.L. (2019). Volatility transmission to the fine wine market. Economic Modelling. 85, 307-316. doi:10.1016/j.econmod.2019.10.017

Ashenfelter, P., Graddy, K. (2011). Sale rates and price movements in art auctions. American Economic Review, 101 (3), 212–216.

Assaf, A., Kristoufek, L., Demir, E., Mitra, S. K. (2021). Market efficiency in the art markets using a combination of long memory, fractal dimension, and approximate entropy measures. Journal of International Financial Markets, Institutions and Money, 71, 101312.

Auer, B.R. (2014). Could diamonds become an investor's best friend? Review of Managerial Science, 8(3), 351–383. doi:10.1007/s11846-013-0108-2

Auer, B.R., & Schuhmacher, F. (2013). Diamonds — A precious new asset? International Review of Financial Analysis, 28, 182–189. doi:10.1016/j.irfa.2013.03.008

Aye, C.G., Chang, T., Chen, W., Gupta, R., Wohar, M., (2018). Testing the efficiency of the art market using quantile-based unit root test with sharp and smooth breaks. Manchester School, 86, 488–511.

Aye, G. C., Chang, T., Chen, W. Y., Gupta, R., & Wohar, M. E. (2017). The efficiency of the art market: Evidence from variance ratio tests, linear and nonlinear fractional integration approaches. International Review of Economics and Finance, 51, 283–294. doi:10.1016/j.iref.2017.06.003

Baillie, R.T., Han Y.W., Myers, R.J., & Song J. (2007). Long memory models for daily and high frequency commodity futures returns. The Journal of Futures Markets, 27(7), 643–668. doi:10.1002/fut.20267

Bernales, A., Reus, L., Valdenegro, V., (2020). Speculative bubbles under supply constraints, background risk and investment fraud in the art market. Journal of Corporate Finance, https://doi.org/10.1016/j.jcorpfin.2020.101746.

Bloomfield, P. (1973) An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Bouri, E. (2014). Beyond the negative relation between return and conditional volatility in the wine market: is fine wine particularly luscious for investors?. International Journal of Wine Business Research.26, (4), 279-294.

Bouri, E., Chang, T., Gupta, R. (2017), Testing the Efficiency of the Wine Market Using Unit Root Tests with Sharp and Smooth Breaks. Wine Economics and Policy, 6(2), 80-87.

Bouri, E., Gupta, R., Wong, W. K., Zhu, Z. (2018). Is wine a good choice for investment?. Pacific-Basin Finance Journal, 51, 171-183.

Bouri, E.I., & Roubaud, D. (2016). Fine Wines and Stocks from the Perspective of UK Investors: Hedge or Safe Haven? Journal of Wine Economics, 11(2), 233–248. doi:10.1017/jwe.2015.10

Caporale G. M. Luis Gil-Alana, Alex Plastun, (2018), Persistence in the cryptocurrency market. Research in International Business and Finance, Volume 46, Pages 141-148 https://doi.org/10.1016/j.ribaf.2018.01.002

Caporale G. M. Luis Gil-Alana, Alex Plastun, (2019) Long memory and data frequency in financial markets Journal of Statistical Computation and Simulation, 89:10, 1763-1779, DOI: 10.1080/00949655.2019.1599377

Caporale, G. M. Luis Gil-Alana, Alex Plastun and Inna Makarenko, (2016), Long memory in the Ukrainian stock market and financial crises. Journal of Economics and Finance. 40, 2, 235-257 http://dx.doi.org/10.1007/s12197-014-9299-x

Chong T.T.L., Lu, C., & Chan W. H. (2012). Long-range dependence in the international diamond market. Economics Letters, 116(3), 401–403. doi:10.1016/j.econlet.2012.04.011

Chu, P. K. K. (2014). Study on the diversification ability of fine wine investment. The Journal of Investing, 23(1), 123-139.

D'Ecclesia, R. L., Jotanovic, V. (2018). Are diamonds a safe haven?. Review of Managerial Science, 12(4), 937-968.

Dahlhaus, R. (1989) Efficient parameter estimation for self-similar process. Annals of Statistics 17, 1749-1766.

Dimson, E., Spaenjers, C. (2014). Investing in emotional assets. Financial Analysts Journal, 70(2), 20-25.

Fama, E., (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. Journal of Finance, 25, 383-417.

Fernandez-Perez, A., Frijns, B., Tourani-Rad, A., Weisskopf, J.-P., (2019). Behavioural Heterogeneity in Wine Investments. Applied Economics, 51 (30), 3236–3255.

Fischer, B.H., Firer, C. (1985). The Risk/Return Characteristics of the Postage Stamp Market. Investment Analysts Journal, 14:26, 31-43.

Gil-Alana, L. A. (2004) The use of the Bloomfield (1973) model as an approximation to ARMA processes in the context of fractional integration, *Mathematical and Computer Modelling*, 39, 429-436.

Gil-Alana, L. A.,& Robinson, P. M. (1997) Testing of unit root and other nonstationary hypotheses in macroeconomic time series. Journal of Econometrics, 80, 2, 241-268. 10.1016/S0304-4076(97)00038-9.

Gil-Alana, L.A., Aye, G.C., & Gupta, R. (2015). Trends and cycles in historical gold and silver prices. Journal of International Money and Finance, 58, 98-109. doi:10.1016/j.jimonfin.2015.08.003

Goetzmann, W.N. (1995). The Informational Efficiency of the Art Market. Managerial Finance, 21(6), 25–34. doi:10.1108/eb018522

Jin, H. J., & Frechette, D. L. (2004). Fractional Integration in Agricultural Futures Price Volatilities. American Journal of Agricultural Economics, 86(2), 432–443. doi:10.1111/j.0092-5853.2004.00589.x

Jurevičienė, D., Jakavonytė, A. (2015). Alternative investments: valuation of wine as a means for portfolio diversification. Business: Theory and Practice, 16(1), 84-93.

Khuntia, S., & Pattanayak, J.K. (2018). Adaptive long memory in volatility of intra-day bitcoin returns and the impact of trading volume. Finance Research Letters, 32, 101077. doi:10.1016/j.frl.2018.12.025

Kumar, A. S. (2021) Adaptive market hypothesis: An empirical analysis of the Wine Market. Wine Economics and Policy,10(2), 99-109. doi: 10.36253/wep-9492

Le Fur, E., (2020). Dynamics of the global fine art market prices. Quarterly Review of Economics and Finance, 76, 167–180.

Liu, J., Cheng, X. Y., Lizhao, Y., & Lai, Y. (2019). Analysis of the efficiency of Hong Kong REITs market based on Hurst exponent. Physica A: Statistical Mechanics and its Applications, 534, 122035. doi:10.1016/j.physa.2019.122035

Masset, P., Henderson, C., (2010). Wine as an Alternative Asset Class. Journal of Wine Economics, 5 (1), 87–118.

Munteanu, A., & Pece, A. (2015). Investigating Art Market Efficiency. Procedia - Social and Behavioral Sciences, 188, 82–88. doi:10.1016/j.sbspro.2015.03.341

Plastun A., Sibande, X., Gupta, R., Wohar, M. (2019), Rise and fall of calendar anomalies over a century, The North American Journal of Economics and Finance, Volume 49, 181-205.

Robinson, P.M. (1994) Efficient tests of nonstationary hypotheses, Journal of the American Statistical Association 89, 1420-1437.

Robinson, P.M. (1995) Gaussian semi-parametric estimation of long-range dependence. Annals of Statistics, 23, 1630-1661.

Scherbina A., Schlusche B. (2014). Asset price bubbles: a survey, Quantitative Finance, 14:4, 589-604.

Sephton, P.S. (2009). Fractional integration in agricultural futures price volatilities revisited. Agricultural Economics, 40(1), 103–111. doi:10.1111/j.1574-0862.2008.00363.x

Veld, C., Veld-Merkoulova, Y. V. (2007). Portfolio diversification benefits of investing in stamps. The Journal of Alternative Investments, 10(1), 56-61.

Zhou, J. (2016). Forecasting REIT volatility with high-frequency data: a comparison of alternative methods. Applied Economics, 1-16. doi:10.1080/00036846.2016.1243215

Zhou, J., & Kang, Z. (2011). A Comparison of Alternative Forecast Models of REIT Volatility. The Journal of Real Estate Finance and Economics, 42(3), 275–294. doi:10.1007/s11146-009-9198-7